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A Multi-Agent Reinforcement That Involves Deep Neuronal Learning for a Healthcare Monitoring System Has Been Canonically Related

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ABSTRACT

Health monitoring systems are collecting the structural responses initiates from ambient and/or external disturbances about health structure depending on the measurement data. The sensors are positioned in structure to determine and record the environmental data. But, failed to improve the accuracy level and time complexity was not reduced by conventional methods. To overcome this work, a Canonical Correlated Multi-Agent Reinforcement Deep Neural Learning (CCMARDNL) Model is performed for patient health monitoring with minimum time consumption. In CCMARDNL Model, Deep neural learning process comprised five layers, namely one input layer, three hidden layers and one output layer for performing patient health monitoring. IoT patient data is gathered from the database and given to the input layer. The input patient data is transmitted to the hidden layer 1. After that, data preprocessing is performed in the hidden layer 1 to remove the data with missing value. It is mainly used to enhance the classification performance and transmitted to the hidden layer 2. Then in hidden layer 2, canonical correlation analysis is calculated between the features and objective for choosing the relevant features. In hidden layer 3, SoftMax activation function is used in CCMARDNL Model to analyze the feature value of the data for performing classification. Finally, the data classification is carried out in the output layer. This in turn helps to improve the performance of patient health monitoring. Performance analysis is performed for different factors namely classification accuracy, classification time, space complexity and error rate with respect to number of patient data when compared to conventional methods.

Keywords: IoT patient data, health monitoring system, classification, canonical correlation analysis, environmental data

1. INTRODUCTION

IoT is the process of connecting computing devices, and people with sensors and actuators to collect data and improve wellness, productivity, and efficiency. IoT health monitoring prevented the disease spread for health diagnosis. A holistic Deep Neural Network-driven IoT smart healthcare technique termed Grey Filter Bayesian Convolution Neural Network (GFB-CNN) was performed in real-time analytics. By the accuracy level was enhanced, the disease diagnosis time consumption was not reduced. A hybrid fuzzy-based decision tree (HFDT) algorithm was proposed in [2] to heart disease prediction at an early stage. But it failed to minimize the error rate by HFDT algorithm.

Virtual patients monitoring was carried out through wearable sensor nodes with medical facility. Android based Health Enabled Remote Terminal (ALERT) system record the data and transmitted to the cloud. But the designed healthcare system failed to improve the performance of medical healthcare to predict the patient's disease at an early stage.

PPG quality assessment approach was determined in IoT-based health monitoring systems. However, the computational complexity level was not reduced by ALERT system. Bi-GRU technique was introduced to categorize structured and unstructured health records to predict the patient stages of ill health. Arithmetically Updated Coot Optimization Algorithm was designed with weights of Bi-GRU. However, the computational cost was not reduced. A lightweight authentication technique was performed with privacy-preserving scheme by fully homomorphic encryption. But it failed to minimize the time complexity. Scalable and reliable artificial intelligence-enabled IoT and edge computing-based healthcare solution was obtained with lesser latency. The system included health-related data with permanent storage and sharing at edge data centers. But space complexity was not minimized by obtained solution.

An ontology reasoning-based healthcare monitoring system termed Do-Care was performed for outdoor and indoor patients from chronic diseases. However, the accuracy level was not enhanced by the Do-Care system. A wearable sensing system was employed comprised of the sensitive strain sensor and rechargeable zinc-air battery on laser-induced graphene (LIG) platform. LIG-based sensing system was employed with high internal powering capability. But the error rate was not reduced.

The problems identified from the above literature are minimum accuracy level, better error rate, improved space complexity, higher time complexity, higher computational complexity, better computational cost and so on. To address these issues, the proposed CCMARDNL Model is obtainable for healthcare monitoring system.

CONTRIBUTION OF THE WORK

The main aim of CCMARDNL Model is to perform efficient patient health monitoring with less time consumption. CCMARDNL Model comprised five layers, namely one input layer, three hidden layers and one output layer for performing patient health monitoring.

- IoT patient data is collected from the input database. The data preprocessing is carried out to remove the patient data with missing value to increase the classification performance.
- The canonical correlation analysis is determined between features and objective for choosing the relevant features. The SoftMax activation function is used in CCMARDNL Model to analyze the feature value of the data for performing classification.
- Performance analysis is performed with different factors like as, classification accuracy, classification time and error rate with respect to number of patient data.

2. METHODOLOGY

The healthcare industry has fast development with major contributors to revenue and employment. Big data comprises a large amount of data to carry out efficient predictive analytics. The disease diagnosis in the human body is employed for efficient physical analysis in hospital. IoT and big data are utilized in healthcare applications to determine the normal and abnormal patient condition. However, the conventional algorithm failed to identify the appropriate attributes over the large dataset. In addition, patient health monitoring is infeasible and inaccurate by using existing methods. As a result, a new model is essential to manage the large amount of patient data in less time. Based on the objective, a novel model called CCMARDNL Model is proposed for performing efficient patient e-health monitoring with less time consumption. The architecture of CCMARDNL Model is shown in figure 1.

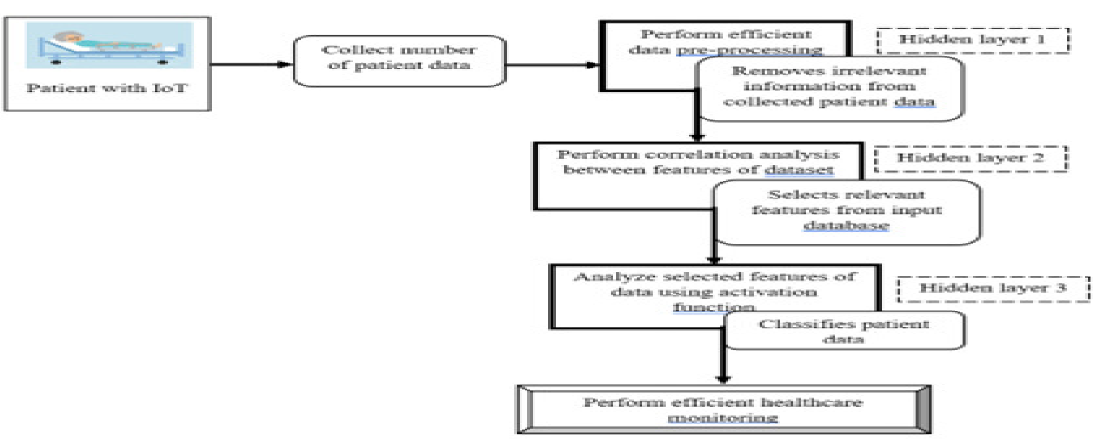

Figure 1Architecture of CCMARDNL Model

From above figure 1, illustrate the architectural diagram of the proposed CCMARDNL Model for carried the accurate healthcare monitoring at initial stage with minimum time complexity. First, IoT devices are positioned at different locations to gather the data from patient. The gathered data are pre-processed and stored in hidden layer 1 for predictive analytics. After that, feature selection is determined in hidden layer 2 by using the correlation analysis to minimum dimensionality. The relevant features are selected, and redundant features are removed from the dataset. The selected important features of patient data are used to classify the patent data into normal or abnormal health conditions in hidden layer 3 with lesser time. Finally, the classified results are utilized for efficient patient disease prediction. The feature selection process and data classification process are explained in the following subsections.

2 .1 Canonical Correlated Multi-Agent Reinforcement Deep Neural Learning

Deep learning is machine learning through neural network to transfer the collection of inputs into set of outputs. Deep learning used the supervised learning with labeled data to handle the complex, higher dimensional raw input data with feature engineering in fields like computer vision as well as natural language processing. Reinforcement learning is a process where agent makes decisions by trial and error. Reinforcement issues are addressed as the Markov decision process (MDP). An agent at every time step is in state, takes the action as well as receives scalar reward and transitions to next state consistent with the environment dynamics. The agent learns policy or map from explanation to actions and improve maximize their returns. From reinforcement learning, the access to the dynamics is performed by sampling. Multi-Agent Reinforcement Deep Neural Learning incorporates the deep learning to address MDPs issues representing the policy. multi-agent reinforcement deep neural learning comprised the different layers is one input and one output layer with three hidden layers. In above figure 2, represents the multi-agent reinforcement deep neural learning classifier with five layers. From proposed CCMARDNL Model, feature information of data is gathered and determined as an input at input layer. In the hidden layer 1, the data pre-processing is carried out. Then, the preprocessed information is sent to thehidden layer 2. In that layer, feature selection is carried out and the selected features are sent to the hidden layer 3. In that layer, data classification is performed for patient disease diagnosis and the result is displayed in the output layer. Each layer has neurons like activating nodes fully linked from one layer to another layer to form entire network. The input layer collects the number of features at time period 't' represented by '$I(t)$'. The nodes are linked from one layer to another layer through dynamic weights. It is symbolized by,

$$In(t) = \sum_{i=1}^{N} f_i * w_{in} + b \quad (1)$$

In above equation (1), '$In(t)$' is the neuron activity at the input layer. 'f_i' is a number of features. 'w_{in}' denotes the initial weight. After that, the received input is transmitted into first hidden layer to perform data pre-processing task with minimum time consumption.

2.1.1 Data Pre-processing

Data pre-processing is an essential method to carry out the data mining process by removing the unnecessary data. Information preprocessing arranges the raw data utilized for another processing. The data preprocessing transfer the data into structured format which helps to efficiently process the classification. The data pre-processing is to enhance the accuracy and lessser time complexity.

2.1.2 Orthogonalized Canonical Correlative Feature Selection Analysis

An OCCFSA is performed in proposed CCMARDNL Model to collect the relevant features for performing efficient predictive analytics. The feature selection analysis is employed to classify and compute the association with two sets. Based on the designed analysis identifies the orthogonal linear combination within each feature that explains the variability. This in turn, thedesigned analysis helped to extract the significant features for accurate predictive analytics.Orthogonalized Canonical Correlative Analysis is carried out to determine the connection between two features 'f_1' and 'f_2' in big dataset. Let us consider that two feature, the canonical correlation analysis identified the linear combinations of features. As a result, canonical correlation is calculated as,

$$\rho \rightarrow \sum f_1\, f_2 = Cov(f_1\,, f_2) \qquad (2)$$

In above equation (2), the covariance matrix is obtained with feature information. Then, the covariance among two features 'f_1' and 'f_2' is determined as,

$$C(f_1\,, f_2\,) = \frac{\sum(f_1 - \overline{f_1})(f_2 - \overline{f_2})}{N} \qquad (3)$$

From (3), 'f_1' and 'f_2'signifies the two feature values of data. '$\overline{a_1}$' is mean of features 'f_1'. '$\overline{f_2}$' denotes the mean of features 'f_2'. 'N' is a total number of the features in dataset. OCCFSA algorithm obtains the correlation with two features. Consequently, OCCFSA algorithm extracts the features with better correlation value for performing efficient data classification process. The algorithmic steps of OCCFSA algorithmis illustrated in below,

// Orthogonalized Canonical Correlative Feature Selection Algorithm

Input: Big Dataset 'D_k', Number of features '$\{f_1, f_2, \dots, f_N\}$'

Output: Select relevant features for predictive analytics

Step 1: Begin

Step 2: **For** each input features 'f_i'

Step 3: Compute covariance '$Cov(f_1\,, f_2\,)$'

Step 4: Calculate canonical correlation 'ρ'

Step 5: $\boldsymbol{If}(\rho > t\square)$ **then**

Step 6: Feature is selected as relevant.

Step 7: **Else**

Step 8: Feature is removed as irrelevant.

Step 9: **End If**

Step 10: **End For**

Step 11: End

Algorithm 1 Orthogonalized Canonical Correlative Feature Selection Algorithm

From algorithm 1, examine the process of Orthogonalized Canonical Correlative Feature Selection algorithm accurately select the relevant features in given dataset for predictive analytics process with better accuracy. Thus, CCMARDNL Model improves the feature selection performance for efficient disease diagnosis. After that, the extracted features are transmitted to the next hidden layer 3. In that layer, the softmax activation analysis is used in CCMARDNL Model for data classification. The softmax activation function is employed in CCMARDNL Model to test the feature values of training patient data and feature values of disease data for classifying the disease with higher accuracy. It is formulated as,

$$SF = \frac{e^{D_i}}{\sum_{j=1}^{K} 1 + e^{D_i}} \qquad (4)$$

In equation (4), 'SF' denotes the SoftMax activation function. 'D_i' is a training patient data. When training patient data is similar totesting disease data, then the patient data is categorized as diseased patient data. Otherwise, the patient data is categorized as normal patient data. The hidden layer 3 result is determined as,

$$Hd(t) = \sum_{k=1}^{n} D_k * w_{in} + [w_{i\square} * Hd(t-1)] \qquad (5)$$

In equation (5), '$Hd(t)$' is a output of hidden layer, '$w_{i\square}$' denotes the weight among input and hidden layer and$Hd(t-1)$ symbolizes preceding hidden layer. Finally, hidden layer was transmitted to output layer. The output layer of CCMARDNL Model is specified as,

$$Ot(t) = w_{o\square} * Hd(t) \qquad (6)$$

In above equation (6), '$Ot(t)$' is the output layer result. 'w_{o}' denotes the weight between hidden layer and output layer. This in turn helps to improve the disease diagnosis performance with better accuracy and minimum error rate. The algorithmic process of Canonical Correlated Multi-Agent Reinforcement Deep Neural Learning is described as,

3. PERFORMANCE ANALYSIS

Performance analysis of proposed in CCMARDNL Model and existing methods are implemented using Python high-level programming language. The existing methods are namely Grey Filter Bayesian Convolution Neural Network (GFB-CNN) [1] and HFDT [2]. The performance of three methods is evaluated using cardiovascular disease dataset obtained from https://www.kaggle.com/sulianova/cardiovascular-disease-dataset. IoT patient data is collected from the database. The objective of proposed CCMARDNL Model is to perform efficient data analysis of the cardiovascular patients. The dataset has 70000 reading with 12 features and 1 target results. The feature information in dataset is given in table 1.

Table 1 Cardiovascular Disease Dataset Information

S. No	Features	Description
1	Age	Integer (years of age)
2	Height	Integer (cm)
3	Weight	Integer (kg)
4	Gender	(1: female; 2:male)
5	Ap_High	Systolic blood pressure
6	Ap_Low	Diastolic blood pressure
7	Cholesterol	(1: normal; 2: above normal; 3: well above normal)
8	Glucose	(1: normal; 2: above normal; 3: well above normal)
9	Smoke	(0:no; 1:yes)
10	Alocohol	(0:no; 1:yes)
11	Physical Activity	(0:no; 1:yes)
12	Cardio_Disease	(0:no; 1:yes)

4. RESULT AND DISCUSSION

In this section, result analysis of proposed CCMARDNL Model and existing Grey Filter Bayesian Convolution Neural Network (GFB-CNN) [1] and HFDT [2] are explained with different parameters like classification accuracy, classification time, error rate and space complexity. The performance results are assessed with tables and graphical illustrations.

4.1 Analysis of Classification Accuracy

Classification accuracy is defined as ratio of number of patient data which are correctly categorize into class to the total number of patient data. The classification accuracy is calculated as,

$$ACC_{CL} = \sum_{i=1}^{N} \left(\frac{D_{CC}}{D_i}\right) * 100 \quad (7)$$

In equation (7), 'ACC_{CL}' is a classification accuracy. 'D_{CC}' is a number of data correctly classified, 'D_i' is a total number of patient data. Classification accuracy is measured in percentage (%).

Table 2 Comparison of Classification Accuracy

Number of Patient Data (Number)	Classification Accuracy (%)		
	GFB-CNN	HFDT	Proposed CCMARDNL Model
7000	92	93.46	98.71
14000	82.14	91.79	98.53
21000	87.62	90.95	98.04
28000	88.89	90	97.86
35000	86.86	88.73	97.66
42000	82.86	87.04	97.38
49000	83.27	84.19	97.55
56000	78.58	82.60	99.64
63000	79.52	81.37	96.90
70000	77.14	80.46	99.75

From Table 2, examine the classification accuracy performance results of three methods, proposed CCMARDNL Model, GFB-CNN [1] and HFDT [2] respectively. The classification accuracy versus number of patient data is explained in above table. For conducting experiments, the number of patient data is varied from 7000 to 70000. With number of patient data, the different runs are carried out to show performance of proposed and existing algorithms. When considering 42000 patient data as input, classification accuracy attained by CCMARDNL Model is 97.38% whereas existing GFB-CNN [1] and existing HFDT [2] attains 82.86% and 87.04% respectively. The above table values represent that classification accuracy is significantly improved by using CCMARDNL Model when compared to existing methods [1], [2].

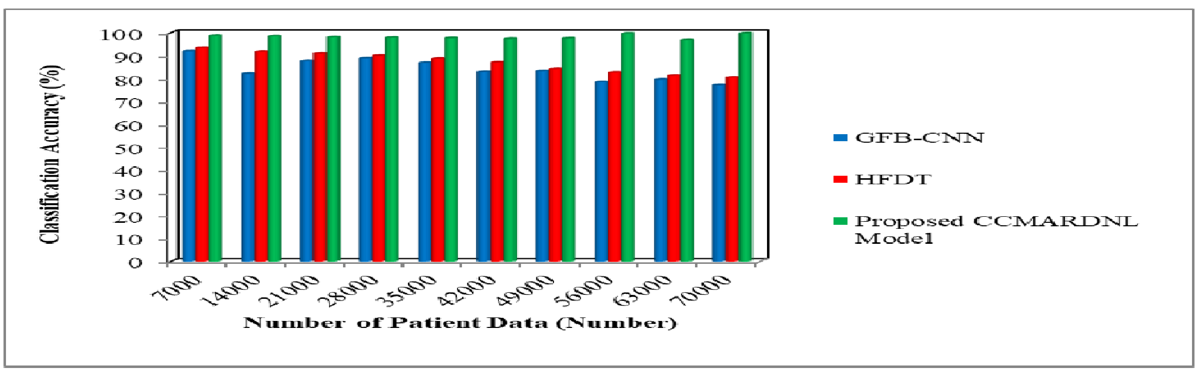

Figure 2 Analysis of Classification accuracy

The simulation results of classification accuracy are shown in figure 2.Figure 2 explains impact of classification accuracy based on varied number of patient data using CCMARDNL Model, existing GFB-CNN [1] and existing HFDT [2]. The green cylinder symbolizes the classification accuracy of CCMARDNL Model whereas blue cylinder and red cylinder represents the classification accuracy of existing GFB-CNN [1] and existing HFDT [2]. As depicted in above graphical representation, CCMARDNL Model attains higher classification accuracy when compared to existing methods. This is because of multi-agent deep learning with data pre-processing, feature selection and data classification process. The data preprocessing eliminates the noisy data and the relevant features are selected through computing relation between features and objectives. Then, the softmax activation function analyzes the feature value of data for efficient classification. This in turn helps to increase the classification accuracy for patient health monitoring. As a result, CCMARDNL Model improves the classification accuracy by 17% and 13% as compared to existing GFB-CNN [1] and existing HFDT [2] respectively.

4.2 Analysis of Error Rate

Error rateis ratio of a number ofpatient data that are wrongly classified into specific class to the total number of patient data. The error rate is formulated as,

$$Err = \sum_{i=1}^{n}\left(\frac{D_{ICC}}{D_i}\right) * 100 \quad (8)$$

In equation (8), 'Err' is an error rate, 'D_{ICC}' denotes the number of data incorrectly classified. The error rate is measured in percentage (%).

From above Table 3, represent the performance results of error rate for three methods, CCMARDNL Model, GFB-CNN [1] and HFDT [2] respectively. The error rate Vs number of patient data is shown in table 3. For experimental consideration, the number of patient data is varied from 7000 to 70000. With number of patient data, the ten different runs are carried out to increase the performance of proposed and existing algorithms. When considering 63000 patient data as input, error rate attained by CCMARDNL Model is 3.1% whereas the existing GFB-CNN [1] and HFDT [2] attains 20.48% and 18.63% respectively. The above table values describe that error rate is significantly reduced using CCMARDNL Model when compared to GFB-CNN [1] and HFDT [2]. The simulation results of error rate are shown in figure 5.

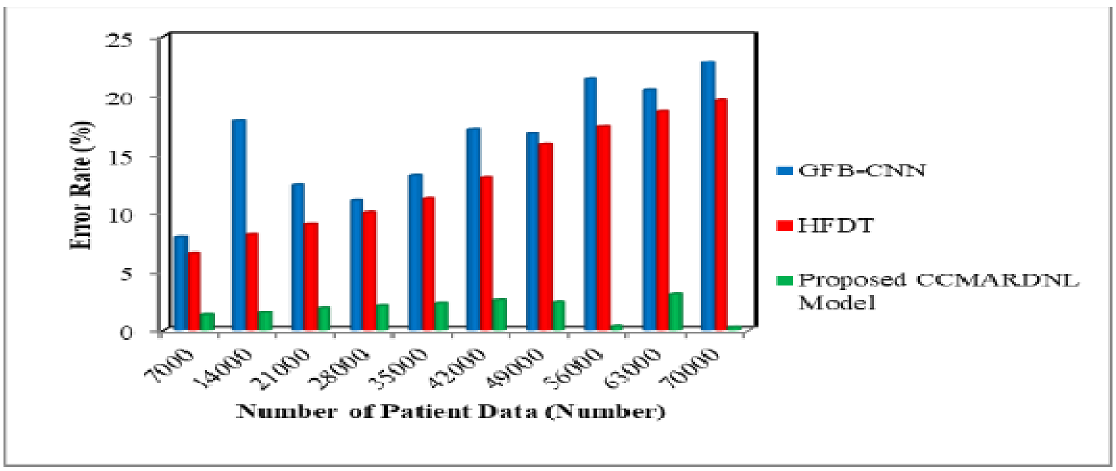

Figure 3 Analysis of Error Rate

From above figure 3, examine the analysis of error rate based on varied number of patient data using proposed CCMARDNL Model, existing GFB-CNN [1] and existing HFDT [2]. The green cylinder symbolizes the error rate of CCMARDNL Model whereas blue cylinder and red cylinder represents the error rate of existing GFB-CNN [1] and existing HFDT [2]. As depicted in above graphical representation, CCMARDNL Model attains lesser error rate when compared to existing methods. This is because of multi-agent reinforcement learning for patient health monitoring with data pre-processing, feature selection and data classification. The data preprocessing removes the noisy data and canonical correlation analysis computes the relation between features and objectives for selecting the relevant features. The softmax activation function analyzes the feature value of data for efficient classification. This in turn helps to reduce the error rate for patient health monitoring. As a result, CCMARDNL Model minimizes the error rate by 87% and 84% as compared to existing [1] and [2] respectively.

4.3 Analysis of Classification Time

Classification time is defined as an amount of time determined to categorize thepatient data as normal patient data or abnormal patient data. Therefore, the classification time is calculated as,

$$CT = \sum_{i=1}^{n} D_i * time[classification] \quad (9)$$

In equation (9), 'CT' is a classification time, 'n' denotes the total number of patient data, $time[classification]$ is a time to classify a patient data. The classification time is measured in milliseconds (ms).

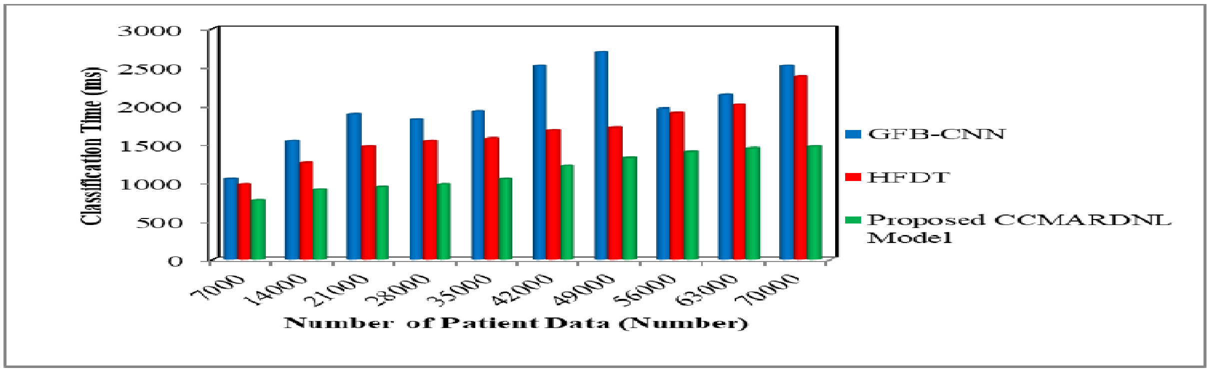

Figure 4 Analysis of Classification Time

For experimental analysis, the number of patient data varied from 7000 to 70000. With different number of patient data, the ten runs are carried out to enhance the performance of proposed and existing algorithms. When considering 21000 patient data as input, classification time consumed by CCMARDNL Model is 945ms whereas the existing GFB-CNN [1] and HFDT [2] attain 1890ms and 1470ms respectively.

5. CONCLUSION

A novel method termed as proposed CCMARDNL Model is performed for patient health monitoring with minimum time consumption. Initially, IoT patient data is gathered from input database. After that, data preprocessing removes the data with missing value for improving classification performance. Next, canonical correlation analysis computes between features and objective for choosing the relevant features. The SoftMax activation function in CCMARDNL Model analyzes the feature value of the patient data for performing classification. This in turn helps to enhance the patient's health monitoring performance. In CCMARDNL Model, achieves improved patient health monitoring performance with lesser time when compared to conventional methods. The performance of CCMARDNL Model is for different factors namely classification accuracy, classification time, space complexity, and error rate when compared with two conventional methods.The performance result illustrates that patient health monitoring provides improved performance with a development of accuracy and minimization of time and space complexity when compared to state-of-the-art works.

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